Reliable Orchard Mapping in Data-Scarce Landscapes

N. Ahmadi Sani[1*], S. Moradi[2], J. Henareh[3], M. Pato[3]

1- Institute of Agriculture, Water, Food, and Nutraceuticals, Mah. C., Islamic Azad University, Mahabad, Iran
2- Department of Agricultural & Natural Resources Development, Faculty of Engineering, Payam Noor University, Tehran, Iran
3- Forests and Rangelands Research Department, West Azerbaijan Agricultural and Natural Resources Research and Education Center, Agricultural Research, Education and Extension Organization, Urmia, Iran
(*- Corresponding Author Email: na.ahmadisani@iau.ac.ir)
https://doi.org/10.22067/jam.2026.96725.1449

Abstract

This study assesses the capability of Sentinel-2A imagery combined with machine-learning classifiers on the Google Earth Engine platform for accurate orchard mapping in the environmentally stressed Sharviran Plain along the southern margin of Lake Urmia, Iran. Random Forest, Support Vector Machine, and Classification and Regression Trees were applied to multispectral bands and selected spectral and vegetation indices, using 836 systematically collected samples from high-resolution imagery and field surveys for training and validation. The study specifically focuses on orchard mapping, with particular emphasis on reliably distinguishing orchards from other agricultural and non-agricultural land-use classes. Results show that orchards cover approximately 11% of the study area, and that the Random Forest classifier achieved the highest performance (Kappa = 0.84) and the best orchard F1-score, demonstrating superior class-level discrimination. Validation against 2023 ground-based orchard statistics showed a low error margin of 2.2%, confirming the reliability of the approach for operational orchard mapping. These findings confirm that integrating Sentinel-2A imagery with machine-learning classifiers on cloud-based platforms offers a robust, reproducible, and cost-efficient framework for orchard mapping in data-scarce and drought-affected regions. The resulting high-resolution orchard maps can effectively support agricultural planning, irrigation management, and evidence-based policy-making in the Lake Urmia basin. Future work may further improve performance by incorporating multi-temporal imagery, additional ecological and socio-economic variables, and advanced models such as deep learning.

Keywords: Machine learning, Orchard mapping, Sentinel 2, Urmia Lake

Introduction

Reliable and spatially explicit orchard maps are essential for agricultural planning, water allocation, and sustainability assessments, particularly in data-poor and drought-affected regions where field-based inventories are limited, costly, or outdated (Younesi, Ahmadi Sani, & Sharafi, 2019). Fruit orchards play a key socio-economic role in such environments, yet they are highly sensitive to water availability, soil degradation, and climatic stress (Sharma *et al.*, 2023; Wang *et al.*, 2023). In semi-arid, perennial-crop systems, limited orchard distribution data hinders effective land and water management and increases policy uncertainty (Fereres & Soriano, 2007).

Remote sensing offers a scalable, cost-effective, and objective alternative to traditional orchard mapping, providing consistent observations over large areas (Sishodia, Ray, & Singh, 2020; Younesi *et al.*, 2019). Improvements in satellite spatial, spectral, and temporal resolution now allow for a more reliable characterisation of heterogeneous agricultural landscapes (Sishodia *et al.*, 2020). Recent studies highlight the strong potential of Sentinel-2 imagery with machine-learning classifiers (ML) for vegetation and agricultural mapping, leveraging its high spatial resolution, red-edge bands, and frequent revisit cycle (Immitzer, Vuolo, & Atzberger, 2016; Phiri *et al.*, 2020). ML algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Trees (CART) have been widely applied in remote sensing classification due to their ability to handle high-dimensional feature spaces and non-linear class boundaries, often outperforming traditional parametric approaches (Huang, Chen, Yu, Huang, & Gu, 2018; Maxwell, Warner, & Fang, 2018). Most Sentinel-2/ML studies focus on Land use/Land cover (LU/LC) mapping, with fewer explicitly targeting orchard mapping and the robust separation of orchards from spectrally similar land uses such as croplands and rangelands (Immitzer *et al.*, 2016; Talukdar *et al.*, 2020).

Recent studies show that Sentinel-2 imagery improves orchard discrimination from other land-cover types, leveraging seasonal phenological differences (Immitzer *et al.*, 2016; Phiri *et al.*, 2020). ML classifiers, particularly RF, consistently achieve high accuracy in orchard boundary delineation from Sentinel-2 data and often outperform other algorithms in heterogeneous landscapes (Belgiu & Drăguţ, 2016; Talukdar *et al.*, 2020). Integrating spectral/vegetation indices with ancillary data (e.g., topography, soil) further enhances performance and reduces orchard vs. non-orchard confusion (Maxwell *et al.*, 2018; Zhao *et al.*, 2024). Despite these advances, sparse orchard distribution, high intra-class variability, and phenological overlap remain challenges that limit regional classifier generalisability (Chen, Ren, Zhang, & Zhao, 2025; Huang *et al.*, 2018). This limitation is especially critical in data-scarce regions, where class imbalance, limited reference data, and phenological overlap remain unresolved challenges (Huang *et al.*, 2018; Maxwell *et al.*, 2018).

Cloud-based platforms such as Google Earth Engine (GEE) have further transformed satellite data processing by enabling large-scale, integrated analysis without the need for local data storage or high-performance computing infrastructure (Biswas, Jobaer, Haque, Islam Shozib, & Limon; Ghosh, Kumar, & Kumari, 2022). GEE provides direct access to extensive multisensory archives, including Sentinel-2 imagery, which—with 13 spectral bands and high spatial resolution—offers valuable information for vegetation monitoring and land-cover discrimination (Phiri *et al.*, 2020).

Despite these technical advances, the practical application of Sentinel-2 imagery and machine-learning classifiers for orchard-specific mapping in data-poor, environmentally stressed regions remains limited, emphasising the need for systematic evaluation to ensure reliable orchard identification (Phiri *et al.*, 2020; Talukdar *et al.*, 2020). This study used Sentinel-2A imagery (10–20 m, 13 bands, pre-corrected) from the 2023, processed in GEE for efficient orchard mapping across the heterogeneous Sharviran Plain.

The Sharviran Plain, located along the southern margin of Lake Urmia in West Azerbaijan, Iran, represents a critical case where these challenges converge. The region is one of Iran's major fruit-producing areas, yet it lies within a severely stressed basin affected by prolonged drought, groundwater depletion, soil salinisation, and the ongoing desiccation of Lake Urmia (AghaKouchak *et al.*, 2015). Although orchards play a central role in local livelihoods and regional agricultural production, reliable, high-resolution orchard maps for the Sharviran Plain are currently lacking, and no previous study has systematically evaluated the performance of Sentinel-2 data and widely used ML classifiers for orchard mapping in this area. As a result, uncertainties remain regarding the orchard's extent, spatial distribution, and its implications for sustainable agricultural and environmental management in the Lake Urmia basin. To address these gaps, this study generates a high-resolution orchard map of the Sharviran Plain using Sentinel-2A imagery within the GEE platform, emphasising orchard identification and discrimination from other land-use classes. It also provides a systematic comparison of three widely used ML classifiers (RF, SVM, and CART) using a consistent feature set in a cloud-based environment. By emphasising reproducibility, class-level performance, and validation against recent ground-based orchard statistics, this work delivers the first validated high-resolution orchard map for the Sharviran Plain and contributes a scalable framework for orchard mapping in data-poor, drought-affected agricultural regions.

Materials and Methods

Study area

The Sharviran Plain (≈70,000 ha) lies along the southern margin of Lake Urmia, Iran, and is a major fruit-producing region, especially for apples. The flat plain features a heterogeneous mosaic of orchards, croplands, rangelands, settlements, and salt flats. With a cold, humid climate (≈1,300 m elevation, 350 mm annual rainfall), horticulture plays a key role in local livelihoods and regional development. Accurate orchard mapping supports production estimates, resource management, and agricultural planning .Figure 1 shows a Sentinel-2 image of the study area and its location in Iran.

Data collection

Sentinel-2A imagery for July–September 2023 was accessed via the GEE platform (Pereira, Lopes, & Pedroso, 2022), providing 13 spectral bands at 10–60 m resolution (Revel *et al.*, 2019; Zhao *et al.*, 2024). Based on prior studies, August imagery was selected for final mapping, as orchard canopies were densest and spectral separability from croplands and rangelands was highest (Phiri *et al.*, 2020; Sishodia *et al.*, 2020).

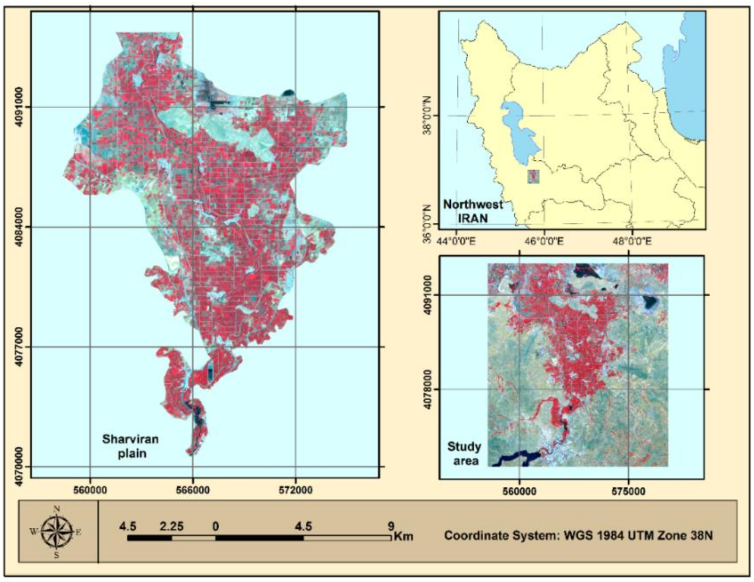

Fig. 1. Sentinel-2 false-colour composite (bands 8–4–3) showing the Sharviran Plain

Methodology

RF, SVM, and CART are widely used non-parametric classifiers for LU/LC mapping (Nery *et al.*, 2016; Schulz *et al.*, 2021; Zhao *et al.*, 2024). CART is simple and interpretable but prone to overfitting (Pande *et al.*, 2024). RF, an ensemble of CART trees, improves robustness and accuracy (Ge *et al.*, 2020; Zhao *et al.*, 2024). SVM effectively handles high-dimensional, non-linear data but requires careful kernel and hyperparameter tuning (Sharma *et al.*, 2023).

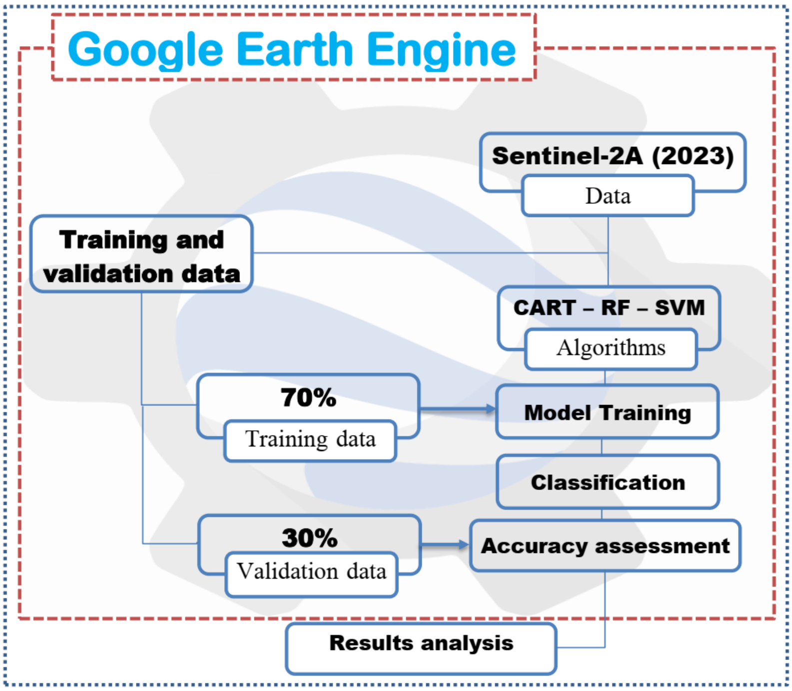

Fig. 2. Overview of the research workflow

Image Processing

Cloud-free, geometrically and atmospherically corrected Sentinel-2A 2023 imagery was processed in GEE, with key spectral indices extracted and combined with original bands to enhance vegetation and land-cover separability (Nigar, Li, Jat Baloch, Alrefaei, & Almutairi 2024; Revel *et al.*, 2019; Yimer, Bouanani, Kumar, Tischbein, & Borgemeister 2024; Table 1).

Table 1- Key indices derived from the Sentinel-2 imagery used in the study

Index	Reference
Normalised Difference Water Index (NDWI)	Yimer *et al.* (2024)
Tasseled Cap Transformation (TCT)	Schulz *et al.* (2021)
Modified Soil-adjusted Vegetation Index (MSAVI)	Ge, Shi, Zhu, Yang, and Hao (2020)
Chlorophyll Vegetation Index (CVI)	Modica, Messina, De Luca, Fiozzo, and Pratico (2020)
Normalised Difference Red Edge (NDRE)	Modica *et al.* (2020)
Ratio Vegetation Index (RVI)	Nigar *et al.* (2024)
Difference Vegetation Index (DVI)	Yimer *et al.* (2024)
Normalised Difference Built-up Index (NDBI)	Tan *et al.* (2021)
Principal Components Analysis (PCA)	Wang *et al.* (2023)
Normalised Difference Vegetation Index (NDVI)	Guzmán, Boumahdi, and Gómez (2022)

To ensure transparency and reproducibility, the same explicit feature set was used for all three classifiers (RF, SVM, and CART). This set included: (i) selected Sentinel-2 spectral bands and (ii) derived spectral and vegetation indices. No classifier-specific subsets were applied, and no feature elimination was performed before training. PCA was utilised only as an auxiliary feature because relying solely on PCA decreased orchard separability. Therefore, both the original features and the PCA components were retained.

Samples dataset

The training and validation datasets were developed and annotated within the GEE platform by integrating high-resolution Google Earth imagery with field survey observations.

A systematic sampling strategy was adopted to ensure uniform spatial coverage across the study area and to capture land-use heterogeneity.

The input data for all classifiers comprised Sentinel-2A imagery (13 spectral bands) and a set of derived spectral and vegetation indices (NDVI, NDWI, MSAVI, NDRE, and PCA components). The target variable was a binary land-cover class (orchard vs. non-orchard), annotated from high-resolution imagery and supported by field observations.

The complete reference dataset was randomly split into training (70%) and independent validation (30%) subsets. The training set was used for model fitting, hyperparameter tuning, and class-weight optimisation, while the validation set was withheld to prevent information leakage and provide an unbiased assessment of classification accuracy, following best practices in remote sensing and machine-learning studies (Aldiansyah & Saputra, 2023; Maxwell *et al.*, 2018).

The resulting dataset showed a clear class imbalance, with more non-orchard samples (482) than orchard samples (82). This class imbalance reflects the dominance and higher spectral heterogeneity of non-orchard land uses. Retaining all majority-class samples preserves spatial representativeness, but may bias results toward non-orchard areas and overestimate their accuracy (Chen *et al.*, 2025).

Alternative strategies, such as random under-sampling or strict stratified sampling, were avoided to preserve spectrally diverse non-orchard information and maintain the systematic sampling design. Instead, a class-weighting strategy was applied during training, assigning higher weights to the minority orchard class, in line with best practices (Nery *et al.*, 2016; Zhao *et al.*, 2024).

Sensitivity analysis with different class-weight settings showed <1% variation in overall accuracy, indicating stable classifier performance despite the imbalanced training data. External validation was performed by comparing the final orchard maps with 2023 ground-based orchard statistics from the Jihad Agricultural Ministry, providing an independent assessment of map reliability.

Model Training and Hyperparameter Settings

Three widely used ML classifiers (RF, SVM, and CART) were applied for orchard mapping in the Sharviran Plain, all implemented within the GEE platform for scalable processing and methodological consistency. Prior to final training, a systematic grid-based exploration of key hyperparameters was conducted for each classifier using the training dataset, varying values within commonly recommended ranges to identify optimal configurations and ensure fair performance comparison (Maxwell *et al.*, 2018; Talukdar *et al.*, 2020).

Model performance during tuning was evaluated using class-specific metrics from the confusion matrix, with emphasis on the F1-score of the orchard class, which balances precision and recall and is especially informative under class imbalance (Chicco & Jurman, 2020). Hyperparameter settings maximising orchard F1-score while maintaining stable overall accuracy were selected as optimal to avoid overfitting and ensure consistent performance across the heterogeneous landscape.

The final configurations were: RF with 100 trees, maximum depth of 15, minimum leaf size of 1, using out-of-bag error for internal validation (Ge *et al.*, 2020; Zhao *et al.*, 2024); SVM with an RBF kernel (C = 1.0, gamma = 0.1) (Talukdar *et al.*, 2020); and CART with a maximum depth of 10 and default GEE parameters to limit overfitting (Aldiansyah & Saputra, 2023). These settings ensured robust orchard discrimination and stable performance across the heterogeneous study area. To assess the stability of the selected hyperparameter configurations, sensitivity analyses were conducted by varying key parameters within reasonable ranges during model training.

Accuracy analysis

Accuracy assessment in remote sensing evaluates the reliability of land-cover classifications by comparing the mapped results with an independent reference or ground-truth dataset (Yi, Zhao, Sun, & Wang, 2024). All accuracy metrics were computed using an independent validation dataset (30% of samples) excluded from training and hyperparameter tuning, ensuring unbiased performance assessment (Maxwell *et al.*, 2018; Patil & Panhalkar, 2023).

Classification performance was assessed using standard confusion-matrix–based metrics, including User's Accuracy (UA), Producer's Accuracy (PA), Overall Accuracy (OA), the Kappa coefficient (Kc), and the F1-score, all calculated on the independent validation dataset. The F1-score balances precision and recall and is particularly informative under class imbalance conditions (Chicco & Jurman, 2020; Patil & Panhalkar, 2023; Tan *et al.*, 2021; Zhao *et al.*, 2024).

A majority filter was then applied to remove isolated pixels and improve spatial coherence. All accuracy metrics were subsequently recalculated using the same independent validation dataset to ensure consistency.

Results and Discussion

Reference data

Classification results were validated using a reference (ground truth) dataset (Yi *et al.*, 2024). The reference samples were generated through manual interpretation of high-resolution imagery within the GEE and supported by field observations. A total of 836 systematically distributed samples were collected, with 564 used for training and 272 reserved for validation (Table 2). This systematic sampling strategy ensured adequate spatial representation of the heterogeneous landscape and improved the reliability of the accuracy assessment.

Table 2- Samples Dataset

Class	Training samples	Validation Samples
Orchard	82	64
Non-Orchard	482	208
Sum	564	272

Model Performance Evaluation

This study evaluated the performance of Sentinel-2A imagery combined with three ML classifiers (CART, RF, and SVM) for discriminating orchard and non-orchard land uses along the southern margin of Lake Urmia. Classification was based on multispectral bands and remote sensing derived indices, and the resulting orchard/non-orchard maps produced by the three classifiers are shown in Figure 3.

The estimated orchard area accounted for 11.03% (7,676 ha) using CART, 11.6% (8,075 ha) using RF, and 11.45% (7,968 ha) using SVM, while non-orchard areas covered 88.97%, 88.4%, and 88.55% of the study area, respectively. A comparative summary of orchard and non-orchard area estimates is presented in Figure 4.

Classification accuracy was evaluated using User's Accuracy (UA), Producer's Accuracy (PA), Overall Accuracy (OA), and the Kappa coefficient (Kc). RF achieved the highest performance (OA = 94%, Kc = 0.84), followed by CART (OA = 91%, Kc = 0.76) and SVM (OA = 89%, Kc = 0.69). Detailed UA and PA values for both classes are reported in Table 3, with consistently higher accuracies observed for the non-orchard class across all classifiers.

To provide a class-balanced evaluation, F1-scores were also calculated. RF obtained the highest orchard F1-score (0.88), outperforming CART (0.82) and SVM (0.75), while RF also yielded the highest non-orchard F1-score (0.96). These results further confirm the superior ability of RF to discriminate orchards from other land uses.

Sensitivity analysis using class weighting showed that overall accuracy varied by less than 1%, indicating stable classifier performance despite class imbalance. All reported accuracy metrics were obtained using the optimised hyperparameter and class-weight configurations summarised in Table 3.

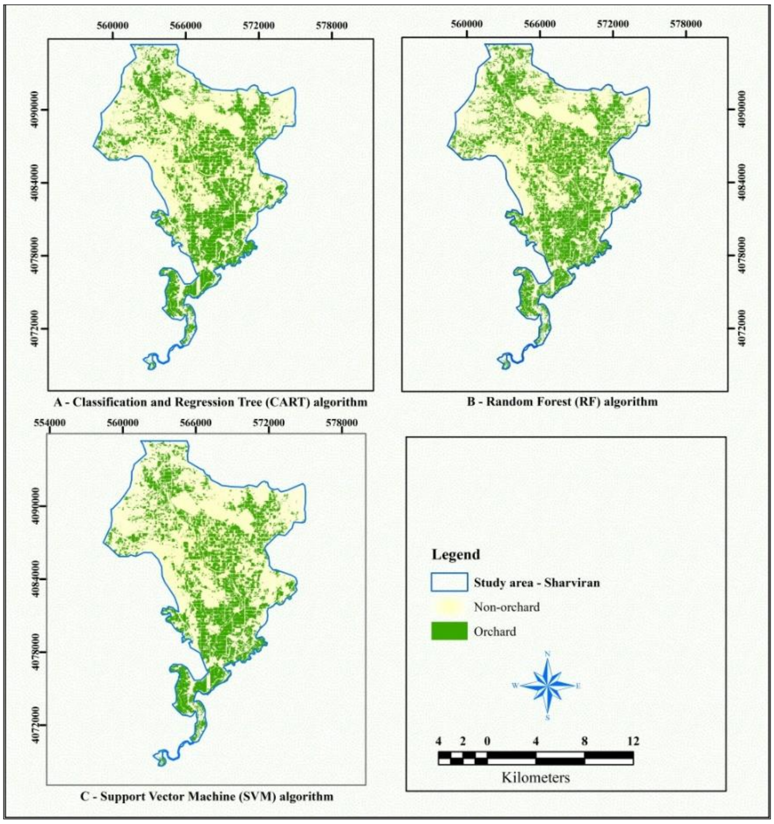

Fig. 3. Spatial distribution of orchard and non-orchard classes derived from different ML classifiers (RF, SVM, and CART)

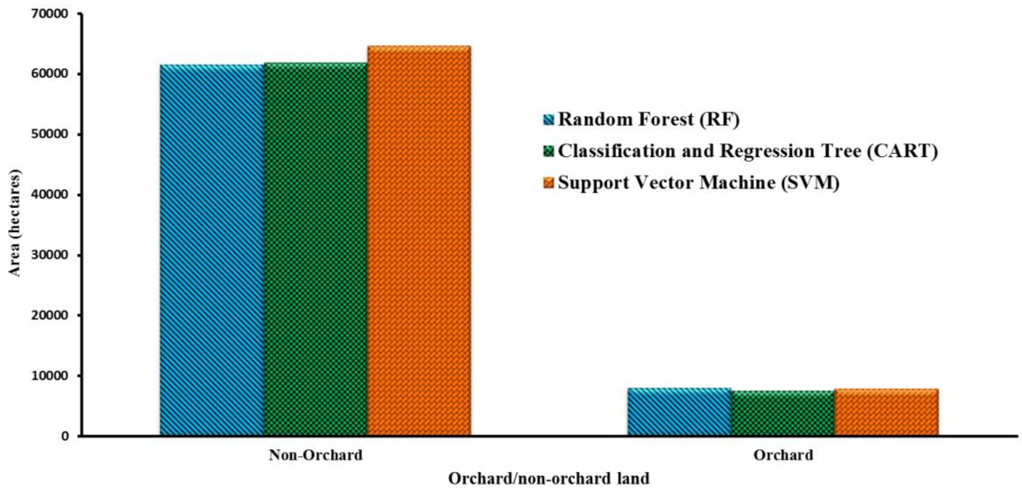

Fig. 4. Estimated orchard and non-orchard area from different LM classifiers (RF, SVM, and CART)

Table 3- Comparative accuracy metrics of orchard and non-orchard classes from different ML classifiers (RF, SVM, and CART)

Algorithm	Class	Hectare	%	UA	PA	OA	Kappa	F1-score
CART	Orchard	7676	11.03	83	81	91	0.76	0.819
	Non-Orchard	61886	88.97	94	95			0.945
RF	Orchard	8075	11.6	90	86	94	0.84	0.879
	Non-Orchard	61487	88.4	95	97			0.960
SVM	Orchard	7968	11.45	82	70	89	0.69	0.755
	Non-Orchard	64594	88.55	91	95			0.930

Discussion

Accurate discrimination between orchard and non-orchard land use is crucial for agricultural monitoring. Classification performance is influenced by algorithm selection, training data quality, landscape heterogeneity, and satellite data characteristics. Recent advances in Earth observation and cloud-based platforms such as GEE have enabled efficient large-scale land-use mapping. In this study, Sentinel-2 Level-2A data within GEE were used to assess orchard mapping performance in the Sharviran Plain.

Three ML classifiers (RF, SVM, and CART) were evaluated using UA, PA, OA, Kappa, and F1-score. RF performed best, achieving the highest OA (94%), Kappa (0.84), and orchard F1-score (0.88), outperforming CART and SVM. This result is consistent with previous studies showing the superior performance of Random Forest for orchard and agricultural mapping with Sentinel-2 data, particularly in heterogeneous landscapes with strong spectral overlap between perennial and annual crops (Aldiansyah & Saputra, 2023; Belgiu & Drăguţ, 2016; Phiri *et al.*, 2020). RF's robustness to spectral noise and moderately imbalanced training data further explains its strong ability to discriminate orchards from spectrally similar land uses such as croplands and rangelands (Belgiu & Drăguţ, 2016; Maxwell *et al.*, 2018). In contrast, the lower accuracy of CART reflects the inherent limitations of single-tree classifiers, particularly their susceptibility to overfitting in complex and heterogeneous landscapes (Camargo, Sano, Almeida, Mura, & Almeida 2019). Similarly, the reduced orchard accuracy of SVM is consistent with previous studies showing that its performance declines under conditions of spectral overlap and class imbalance, which are common in orchard mapping at regional scales (Chen *et al.*, 2025; Nigar *et al.*, 2024).

Results indicate that orchards occupy more than 11% of the Sharviran Plain, highlighting the substantial role of horticulture in a region affected by water scarcity, soil salinity, and ecosystem degradation associated with the desiccation of Lake Urmia. This proportion is comparable to orchard coverage reported in other semi-arid regions of the Middle East and South Asia, where perennial horticulture typically accounts for approximately 8–15% of cultivated land, depending on water availability and management intensity (Patil & Panhalkar, 2023; Talukdar *et al.*, 2020). Accurate orchard mapping is therefore essential for sustainable water allocation, soil management, and regional agricultural planning, particularly in water-stressed basins where misestimation of perennial crop extent can directly influence irrigation demand assessments and groundwater management strategies (Guzmán *et al.*, 2022; Patil & Panhalkar, 2023). Although all classifiers produced similar spatial patterns, RF consistently achieved the highest performance, in agreement with previous Sentinel-based orchard and cropland mapping studies (Aldiansyah & Saputra, 2023; Oo *et al.*, 2022; Phiri *et al.*, 2020; Talukdar *et al.*, 2020; Zhao *et al.*, 2024).

Accuracy values were approximately 7–10% lower than those reported in some previous studies, likely due to higher landscape heterogeneity, class complexity, and differences in reference data (Nigar *et al.*, 2024; Sarker, 2021). Despite class imbalance, sensitivity analysis showed less than 1% variation in overall accuracy, confirming the stability and robustness of the RF classifier, consistent with earlier findings on ensemble methods (Ge *et al.*, 2020; Zhao *et al.*, 2024). However, as noted in previous studies, class imbalance may still affect class-specific performance, highlighting the importance of reporting F1-scores alongside overall accuracy (Chicco & Jurman, 2020).

Integrating Sentinel-2 spectral and vegetation indices improved classification accuracy by about 5%, consistent with previous findings (Yimer *et al.*, 2024). Similar improvements have been reported in orchard and perennial crop mapping studies, where vegetation indices reduced spectral confusion between orchards and annual croplands and enhanced class separability in heterogeneous landscapes (Aldiansyah & Saputra, 2023). Spatial agreement analysis showed an 84% overlap between RF and CART results, indicating consistent and reliable mapping despite differences among classifiers (Patil & Panhalkar, 2023).

Comparable spatial consistency among ML classifiers has been reported in previous studies (Oo *et al.*, 2022). In this study, the final orchard map showed strong agreement with 2023 ground-based orchard statistics for Mahabad County, with only a 2.2% error, which is comparable to or better than discrepancies reported in earlier satellite-based validation studies (Sarker, 2021; Zhao *et al.*, 2024). Overall, the achieved accuracies are consistent with Sentinel-2–based orchard and cropland mapping studies reporting OA > 90%, highlighting the reliability of integrating ML classifiers with Sentinel-2 imagery in cloud-based platforms such as GEE, particularly in data-scarce regions (Phiri *et al.*, 2020; Talukdar *et al.*, 2020; Zhao *et al.*, 2024).

Despite recognition of the ecological and economic value of rural landscapes, limited research has examined how landscape configuration affects provisioning ecosystem services in agricultural areas. This study addresses this gap by delivering high-resolution orchard maps that support future analyses of landscape structure, ecosystem services, and sustainable agricultural planning (Guzmán *et al.*, 2022).

Although overall accuracy was high, it is strongly influenced by the majority non-orchard class and can mask residual errors in the minority orchard class in imbalanced datasets (Chicco & Jurman, 2020). Similar overestimation of majority classes has been reported in other land-cover and crop-mapping studies, where high overall accuracy concealed important errors in minority classes (Chen *et al.*, 2025).

The consistently higher UA and PA for the non-orchard class across all classifiers indicate a tendency toward majority-class bias, a common limitation in imbalanced land-cover classification (Chen *et al.*, 2025; Sarker, 2021). From a practical perspective, remaining confusion between orchards and spectrally similar land uses (e.g., irrigated croplands) can affect decision-making: overestimation may inflate irrigation demand estimates, while underestimation may lead to insufficient water and agricultural resource allocation (Guzmán *et al.*, 2022; Patil & Panhalkar, 2023).

Previous studies in drought-prone agricultural regions indicate that even minor spatial errors in orchard maps can cause significant uncertainty in water-demand estimates and policy planning, highlighting the importance of explicitly communicating uncertainty in operational mapping products (Guzmán *et al.*, 2022; Patil & Panhalkar, 2023).

These issues are particularly critical in drought-affected and data-scarce regions such as the Lake Urmia basin, where management decisions are highly sensitive to spatial uncertainty (Younesi *et al.*, 2019; Wang *et al.*, 2023). Although Random Forest achieved the highest overall accuracy, Kappa coefficient, and orchard F1-score, CART and SVM showed lower sensitivity to the orchard class, highlighting the importance of class-level evaluation (Belgiu & Drăguţ, 2016; Maxwell *et al.*, 2018). Overall, these results emphasise that class imbalance and classification uncertainty should be explicitly considered when interpreting orchard maps and translating them into policy and management decisions.

Conclusion

This study demonstrates that integrating Sentinel-2A imagery with ML classifiers within the GEE platform provides a reliable and operational framework for orchard mapping in the Lake Urmia basin. Among the evaluated methods, Random Forest achieved the highest performance (OA = 94%, Kappa = 0.84) and the strongest class-level reliability, confirming its suitability for heterogeneous agricultural landscapes such as the Sharviran Plain. By explicitly targeting orchard identification and discrimination from other land-use classes, this work extends existing Sentinel-2/ML studies beyond general LU/LC mapping. Results indicate that orchards occupy approximately 11% of the study area, with RF achieving the highest orchard F1-score (0.88) and a low error margin (2.2%) relative to ground-based statistics.

Despite the high overall accuracy achieved, the use of single-date Sentinel-2 imagery and class imbalance in the training data may have introduced minor biases, particularly affecting predictions of the dominant non-orchard class. Nonetheless, the resulting high-resolution orchard maps provide valuable spatial information for sustainable land and water management, irrigation planning, productivity assessment, and evidence-based decision making in drought-affected and ecologically sensitive regions such as the Lake Urmia Basin. Future studies should integrate multi-temporal imagery, additional ecological, hydrological, topographic, and socio-economic variables, and advanced approaches such as deep learning to better capture phenological dynamics and further reduce classification uncertainty.

Overall, this study demonstrates that integrating Sentinel-2 imagery with cloud-based machine-learning methods provides a cost-effective, scalable, and reproducible framework for orchard mapping in data-scarce regions. By producing the first high-resolution orchard map of the Sharviran Plain and validating it against ground-based statistics, the research addresses a clear geographical and methodological gap and establishes a robust baseline for sustainable agricultural planning and environmental restoration in the Lake Urmia basin.

Author Contributions

All authors were involved in the conception and design of the study, as well as in the analysis and interpretation of the data. The drafting of the manuscript was carried out collaboratively by all authors. All authors critically revised the paper for important intellectual content, approved the final version to be published, and agree to be accountable for all aspects of the work.

References

1. AghaKouchak, A., Norouzi, H., Madani, K., Mirchi, A., Azarderakhsh, M., Nazemi, A., ..., & Hasanzadeh, E. (2015). Aral Sea syndrome desiccates Lake Urmia: call for action. *Journal of Great Lakes Research, 41(1),* 307-311. https://doi.org/10.1016/j.jglr.2014.12.007
2. Aldiansyah, S., & Saputra, R. A. (2023). Comparison of machine learning algorithms for land use and land cover analysis using Google Earth engine (Case study: Wanggu watershed). *International Journal of Remote Sensing and Earth Sciences (IJReSES)*, *19*(2), 197-210. https://doi.org/10.30536/j.ijreses.2022.v19.a3803
3. Belgiu, M., & Drăguț, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing, 114,* 24-31. https://doi.org/10.1016/j.isprsjprs.2016.01.011
4. Biswas, J., Jobaer, M. A., Haque, S. F., Islam Shozib, M. S., & Limon, Z. A. (2023). Mapping

and monitoring land use land cover dynamics employing Google Earth Engine and machine learning algorithms on Chattogram, Bangladesh. *Heliyon*, *9*(11), e21245. https://doi.org/10.1016/j.heliyon.2023.e21245

5. Camargo, F. F., Sano, E. E., Almeida, C. M., Mura, J. C., & Almeida, T. (2019). A comparative assessment of machine-learning techniques for land use and land cover classification of the Brazilian tropical savanna using ALOS-2/PALSAR-2 polarimetric images. *Remote Sensing*, *11*(13), 1600. https://doi.org/10.3390/rs11131600
6. Chen, P., Ren, Y., Zhang, B., & Zhao, Y. (2025). Class Imbalance in the Automatic Interpretation of Remote Sensing Images: A Review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. https://doi.org/10.1109/JSTARS.2025.3555567
7. Chicco, D., & Jurman, G. (2020). The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC Genomics, 21(1)*, 6. https://doi.org/10.1186/s12864-019-6413-7
8. Fereres, E., & Soriano, M. A. (2007). Deficit irrigation for reducing agricultural water use. *Journal of Experimental Botany*, *58*(2), 147-159. https://doi.org/10.1093/jxb/erl165
9. Ge, G., Shi, Z., Zhu, Y., Yang, X., & Hao, Y. (2020). Land use/cover classification in an arid desert-oasis mosaic landscape of China using remote sensed imagery: Performance assessment of four machine learning algorithms. *Global Ecology and Conservation*, 22, e00971. https://doi.org/10.1016/j.gecco.2020.e00971
10. Ghosh, S., Kumar, D., & Kumari, R. (2022). Cloud-based large-scale data retrieval, mapping, and analysis for land monitoring applications with google earth engine (GEE). *Environmental Challenges*, 9, 100605. https://doi.org/10.1016/j.envc.2022.100605
11. Guzmán, G., Boumahdi, A., & Gómez, J. A. (2022). Expansion of olive orchards and their impact on the cultivation and landscape through a case study in the countryside of Cordoba (Spain). *Land Use Policy*, *116*, 106065. https://doi.org/10.1016/j.landusepol.2022.106065
12. Huang, Y., Chen, Z., Yu, T., Huang, X., & Gu, X. (2018). Agricultural remote sensing big data: Management and applications. *Journal of Integrative Agriculture*, *17*(9), 1915-1931. https://doi.org/10.1016/S2095-3119(17)61859-8
13. Immitzer, M., Vuolo, F., & Atzberger, C. (2016). First experience with Sentinel-2 data for crop and tree species classifications in central Europe. *Remote sensing*, *8*(3), 166. https://doi.org/10.3390/rs8030166
14. Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, *39*, 2784-2817. https://doi.org/10.1080/01431161.2018.1433343
15. Modica, G., Messina, G., De Luca, G., Fiozzo, V., & Pratico, S. (2020). Monitoring the vegetation vigor in heterogeneous citrus and olive orchards. A multiscale object-based approach to extract trees' crowns from UAV multispectral imagery. *Computers and Electronics in Agriculture*, *175*, 105500. https://doi.org/10.1016/j.compag.2020.105500
16. Nery, T., Sadler, R., Solis-Aulestia, M., White, B., Polyakov, M., & Chalak, M. (2016, July). Comparing supervised algorithms in Land Use and Land Cover classification of a Landsat time-series. In *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 5165-5168). IEEE. https://doi.org/10.1109/IGARSS.2016.7730346
17. Nigar, A., Li, Y., Jat Baloch, M. Y., Alrefaei, A. F., & Almutairi, M. H. (2024). Comparison of machine and deep learning algorithms using Google Earth Engine and Python for land classifications. *Frontiers in Environmental Science*, *12*, 1378443. https://doi.org/10.3389/fenvs.2024.1378443
18. Oo, T. K., Arunrat, N., Sereenonchai, S., Ussawarujikulchai, A., Chareonwong, U., & Nutmagul, W. (2022). Comparing four machine learning algorithms for land cover

classification in gold mining: A case study of Kyaukpahto Gold Mine, Northern Myanmar. *Sustainability*, *14*(17), 10754. https://doi.org/10.3390/su141710754

19. Pande, C. B., Diwate, P., Orimoloye, I. R., Sidek, L. M., Pratap Mishra, A., Moharir, K. N., Pal, S. C., Alshehri, F., & Tolche, A. D. (2024). Impact of land use/land cover changes on evapotranspiration and model accuracy using Google Earth engine and classification and regression tree modeling. *Geomatics, Natural Hazards and Risk*, *15*(1), 2290350. https://doi.org/10.1080/19475705.2023.2290350
20. Patil, A., & Panhalkar, S. (2023). A Comparative analysis of machine learning algorithms for land use and land cover classification using google earth engine platform. *Journal of Geomatics*, *17*(2), 226-233. https://doi.org/10.58825/jog.2023.17.2.96
21. Pereira, S. C., Lopes, C., & Pedroso, J. P. (2022). Mapping cashew orchards in cantanhez national park (Guinea-Bissau). *Remote Sensing Applications: Society and Environment*, 26, 100746. https://doi.org/10.1016/j.rsase.2022.100746
22. Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V. R., Murayama, Y., & Ranagalage, M. (2020). Sentinel-2 Data for Land Cover/Use Mapping: A Review. *Remote Sensing*, *12*, 2291. https://doi.org/10.3390/rs12142291
23. Revel, C., Lonjou, V., Marcq, S., Desjardins, C., Fougnie, B., Coppolani-Delle Luche, C., Guilleminot, N., Lacamp, A., Lourme, E., Miquel, Ch., & Lenot, X. (2019). Sentinel-2A and 2B absolute calibration monitoring. *European Journal of Remote Sensing*, *52*(1), 122-137. https://doi.org/10.1080/22797254.2018.1562311
24. Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Computer Science*, *2*, 160. https://doi.org/10.1007/s42979-021-00592-x
25. Schulz, D., Yin, H., Tischbein, B., Verleysdonk, S., Adamou, R., & Kumar, N. (2021). Land use mapping using Sentinel-1 and Sentinel-2 time series in a heterogeneous landscape in Niger, Sahel. *ISPRS Journal of Photogrammetry and Remote Sensing*, *178*, 97-111. https://doi.org/10.1016/j.isprsjprs.2021.06.005
26. Sharma, V., Sharma, D., Tsai, M. L., Ortizo, R. G. G., Yadav, A., Nargotra, P., ..., & Dong, C. D. (2023). Insights into the recent advances of agro-industrial waste valorization for sustainable biogas production. *Bioresource Technology*, 129829. https://doi.org/10.1016/j.biortech.2023.129829
27. Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of Remote Sensing in Precision Agriculture: A Review. *Remote Sensing*, *12*(19), 1-36. https://doi.org/10.3390/rs12193136
28. Talukdar, S., Singha, P., Mahato, S., Shahfahad, Pal, S., Liou, Y-A., & Rahman, A. (2020). Land-Use Land-Cover Classification by Machine Learning Classifiers for Satellite Observations—A Review. *Remote Sensing*, *12*(7), 1135. https://doi.org/10.3390/rs12071135
29. Tan, J., Zuo, J., Xie, X., Ding, M., Xu, Z., & Zhou, F. (2021). MLAs land cover mapping performance across varying geomorphology with Landsat OLI-8 and minimum human intervention. *Ecological Informatics*, *61*, 101227. https://doi.org/10.1016/j.ecoinf.2021.101227
30. Wang, Y., Han, X., Yan, W., Cheng, L., Dang, X., & Liu, W. (2023). Apple trees can extract soil water from both deep layers and neighboring cropland in the tableland region of Chinese Loess Plateau. *CATENA*, *232*, 107396. https://doi.org/10.1016/j.catena.2023.107396
31. Yi, C., Zhao, X., Sun, Q., & Wang, Z. (2024). Assessing the accuracy of remote sensing data products: A multi-granular spatial sampling method. *Future Generation Computer Systems*, *159*, 151-160. https://doi.org/10.1016/j.future.2024.04.062
32. Yimer, S. M., Bouanani, A., Kumar, N., Tischbein, B., & Borgemeister, C. (2024). Comparison of different machine-learning algorithms for land use land cover mapping in a heterogenous landscape over the Eastern Nile River basin, Ethiopia. *Advances in Space Research*, *74*(5), 2180-2199. https://doi.org/10.1016/j.asr.2024.06.010
33. Younesi, B., Ahmadi Sani, N., & Sharafi, S. (2019). Evaluation of IRS-P6 Images for Orchards

Area Estimating. *Iranian Journal of Remote Sensing and GIS*, *11*(1), 113-126. https://doi.org/10.52547/gisj.11.1.113

34. Zhao, Z., Islam, F., Waseem, L. A., Tariq, A., Nawaz, M., Islam, I. U., Bibi, T., Rehman, N. U., Ahmad, W., Aslam, R. W., Raza, D., & Hatamleh, W. A. (2024). Comparison of three machine learning algorithms using google earth engine for land use land cover classification. *Rangeland Ecology & Management*, *92*, 129-137. https://doi.org/10.1016/j.rama.2023.10.007

تهیه نقشه قابل‌اعتماد باغات در چشم‌اندازهای کم‌داده

ناصر احمدی ثانی[1*]، سهراب مرادی[2]، جلال هناره[3]، مجید پاتو[3]

تاریخ دریافت: ۱۴۰۴/۰۹/۰۵
تاریخ پذیرش: ۱۴۰۴/۱۰/۲۴

چکیده

این مطالعه به تلفیق تصاویر سنتینل–A۲ و طبقه‌بندی‌کننده‌های ماشین یادگیری برای تهیه نقشه باغات در بستر سکوی گوگـل ارث در منطقـه‌ای تحت تأثیر تنش شرایط محیطی (دشت شارویران در جنوب دریاچه ارومیه) می‌پردازد. طبقه‌بندی‌کننده‌های جنگل تصادفی، ماشین بردار پشتیبان و درخت رگرسیون و طبقه‌بندی روی باندهای چندطیفی و شاخص‌های گیاهی و طیفی منتخب با اسـتفاده از ۸۳۶ نمونـه (تعلیمـی و اعتبارسـنجی) سیسـتماتیک حاصل از تصاویر با اندازه تفکیک بالا و نقشه‌برداری زمینی به‌کار برده شـدند. ایـن مطالعـه روی تشـخیص دقیـق باغـات از کاربری‌هـای کشـاورزی و غیرکشاورزی تمرکز دارد. نتایج نشان می‌دهد که باغات حدود ۱۱٪ منطقه مورد مطالعه را پوشش می‌دهد و طبقه‌بندی‌کننده جنگل تصادفی بـا ضـریب کاپای ۰/۸۴ و بهترین F1-score، بالاترین کارآیی را دارد. اعتبارسنجی نتایج با استفاده از برداشت‌های میدانی باغات، خطای کمـی در حـدود ۲/۲٪ را نشان داد. این یافته‌ها نشان می‌دهد که تلفیق تصاویر سنتینل-A۲ با طبقه‌بندی‌کننده‌های ماشین یادگیری، یک چهارچوب توانمند، قابل‌تکرار و کم‌هزینه را برای تهیه نقشه باغات در مناطق با کمبود داده و تحت تأثیر تنش‌های محیطی، پیشنهاد می‌دهد. نقشه‌های باغات با تفکیک مکانی بالا به‌طور مؤثری می‌توانند برای برنامه‌ریزی کشاورزی، مدیریت آبیاری و تصمیم‌سازی مبتنی بر شواهد در حوضه دریاچه ارومیه استفاده شوند. مطالعات آینده می‌توانـد بـا استفاده از تصاویر چندزمانه، متغیرهای اجتماعی–اقتصادی و بوم‌شناختی و مدل‌های پیشرفته ازجمله یادگیری عمیق گسترش داده شود.

واژه‌های کلیدی: تهیه نقشه باغات، دریاچه ارومیه، سنتینل ۲، ماشین یادگیری

۱- دانشکده کشاورزی، آب، غذا و فراسودمندها، واحد مهاباد، دانشگاه آزاد اسلامی، مهاباد، ایران
۲- گروه توسعه کشاورزی و منابع طبیعی، دانشکده فنی و مهندسی، دانشگاه پیام نور، تهران، ایران
۳- گروه تحقیقات جنگل‌ها و مراتع، مرکز تحقیقات و آموزش کشاورزی و منابع طبیعی آذربایجان غربی، سازمان توسعه و آموزش، ارومیه، ایران
(*- نویسنده مسئول: Email: na.ahmadisani@iau.ac.ir)

https://doi.org/10.22067/jam.2026.96725.1449